Optimal Selection and Placement of Green Infrastructure in Urban Watersheds for PCB Control

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Abstract: San Francisco Bay and its watersheds are polluted by legacy polychlorinated biphenyls (PCBs), resulting in the establishment of a total maximum daily load (TDML) that requires a 90% PCB load reduction from municipal stormwater. Green infrastructure (GI) is a multi-benefit solution for stormwater management, potentially addressing the TMDL objectives, but planning and implementing GI cost-effectively to achieve management goals remains a challenge and requires an integrated watershed approach. This study used the nondominated sorting genetic algorithm (NSGA-II) coupled with the Stormwater Management Model (SWMM) to find near-optimal combinations of GIs that maximize PCB load reduction and minimize total relative cost at a watershed scale. The selection and placement of three locally favored GI types (bioretention, infiltration trench, and permeable pavement) were analyzed based on their cost and effectiveness. The results show that between optimal solutions and nonoptimal solutions, the effectiveness in load reduction could vary as much as 30% and the difference in total relative cost could be well over $100 million. Sensitivity analysis of both GI costs and sizing criteria suggest that the assumptions made regarding these parameters greatly influenced the optimal solutions. **DOI: 10.1061/JSWBAY.0000876.**

Introduction

Water quality in the San Francisco Bay and its watershed is degraded by polychlorinated biphenyls (PCBs), mercury (Hg), pesticides, and a number of other pollutants associated with stormwater runoff (Gilbreath and McKee 2015; McKee and Gilbreath 2015; McKee et al. 2017). PCBs are of particular concern because they are toxic, persist in the environment, and accumulate in the tissue of fish, wildlife, and humans, causing a variety of adverse health effects (Davis et al. 2007). Much of the PCB pollution in the San Francisco Bay watersheds happened decades ago, before the potential health and environmental effects of PCBs were widely known, but the legacy of past use is still found in polluted patches across the urban landscape, mixed into the sediment of the Bay, and contaminating the Bay food web (Davis et al. 2007).

Urban runoff is a significant pathway for PCB entry into the Bay. PCBs are transported to the Bay mainly in particulate form in surface water (Gilbreath and McKee 2015; McKee et al. 2017). The main sources to urban runoff include contaminated sediment and water derived from older industrial and manufacturing areas where PCBs were used in electrical equipment, plasticizers, hydraulic oils and lubricants, heat transfer, and petroleum additives prior to bans in the late 1970s (Erickson and Kaley 2011). Additional sources to urban runoff include runoff from illicit waste dumping and remodeling and demolition sites where there are PCB residues in waste-containing caulk (Klosterhaus et al. 2014). Collective urban runoff loads to the Bay from these sources and pathways is estimated to be >15 kg annually (Davis et al. 2007). In response to this persistent problem, the San Francisco Bay Regional Water Quality Control Board adopted a PCB total maximum daily load (TMDL) for San Francisco Bay that requires a 90% PCB load reduction from municipal stormwater over a 20-year timeframe to accelerate the recovery of the Bay from decades of PCB contamination (SFBRWQCB 2007).

Reducing PCBs and other pollutants in stormwater runoff is complex and needs to rely on costly engineering, especially in highly developed urban environments, where often decades or a century or more of infrastructure has already shaped the landscape. Distributed stormwater runoff management using green infrastructure (GI) is emerging as a multibenefit solution that can address both stormwater quality and quantity concerns (McNett et al. 2011; David et al. 2015). The removal of PCBs by GI is primarily through the capture of suspended particles by settling or filtration, as with other hydrophobic urban pollutants such as heavy metals (David et al. 2015). Given the particulate nature of PCBs and observations for phosphorus and heavy metals including Cu, Pb, and Zn, capture through filtration and adsorption most likely occurs in the first 30-cm surface layers of the engineered soil media within bioretention systems (Dechesne et al. 2005; Li and Davis 2008; Komlos and Traver 2012). Therefore, even if systems are designed to exfiltrate, PCBs are unlikely to enter the groundwater system. Groundwater pathways and leaching to groundwater are accordingly not a concern.

Consistent with a nationwide trend, stormwater retrofit using GI is specifically identified in the Bay Area stormwater permit, National Pollutant Discharge Elimination System (NPDES) Permit

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No. CAS612008, as a management measure to reduce the loads of PCBs and other pollutants getting to San Francisco Bay. However, although these pollution issues are common to all Bay Area municipal agencies, widespread implementation of GI is slow and hindered by a lack of watershed-based planning for efficient GI retrofit siting and determinations for the most cost-effective management strategies to achieve desired load reductions in compliance with the permit. Therefore, there is a need for a holistic approach that can facilitate the identification of optimal GI solutions based on their potential effectiveness in reducing stormwater runoff and pollutant loads.

Optimal selection and placement of traditional Best Management Practices (BMPs) for watershed-scale management of stormwater pollutants has been the subject of many previous studies (Bekele and Nicklow 2005; Perez-Pedini et al. 2005; Arabi et al. 2006; Maringanti et al. 2009, 2011; Rodriguez et al. 2011; Ahmadi et al. 2013). These studies employed a well-established, integrative framework that combines a watershed model with a multiobjective optimization algorithm to identify cost-effective solutions among numerous and complex alternatives. Bekele and Nicklow (2005) used an evolutionary algorithm coupled with the Soil and Water Assessment Tool (SWAT) to determine the trade-off among multiple ecosystem service objectives and economic goals associated with agricultural commodity production. Perez-Pedini et al. (2005) combined an event-based, distributed hydrologic model with a genetic algorithm to explore the optimal location of infiltration-based BMPs for stormflow peak reduction. Arabi et al. (2006) compared two approaches to developing nonpoint source pollution management plans and found that reduction of sediment, phosphorus, and nitrogen loads could be achieved more cost effectively by optimizing BMPs using SWAT and genetic algorithm, rather than relying on a traditional approach targeting critical source areas. In a similar fashion, Maringanti et al. (2009, 2011), Rodriguez et al. (2011), and Ahmadi et al. (2013) all applied a multiobjective genetic algorithm [nondominated sorting genetic algorithm (NSGA-II)] in combination with SWAT to provide trade-off curves (optimal fronts) between nonpoint source pollutant reduction and cost at the watershed scale. These studies generally considered reductions in nutrients and sediment in agricultural watersheds or low-density urban areas. However, highly urbanized catchments present a different set of problems than agricultural areas with different pollutants and severely limited space available for retrofitting due to the existing development. For example, in the dense older development areas around San Francisco Bay, PCBs are the focus pollutants (Davis et al. 2007) but there is limited space and uncertainty on which types of GI may be applicable and cost effective.

In recent years, the selection and placement of GI in urban watersheds has gotten some traction, but the number of studies remain scarce. Zare et al. (2012) developed the multiobjective optimization of urban runoff quality and quantity control using NSGA-II and the Storm Water Management Model (SWMM) in an urban watershed, with a mixed GI types (rain barrel, porous pavement area, bioretention) and different land-use areas as decision variables. Giacomoni (2015) and Zhang et al. (2013) both used SWMM and multiobjective optimization to identify the near-optimal trade-off between the total low-impact development costs and runoff reduction in urbanized watersheds. These recent studies on urban watersheds were largely focused on stormwater runoff control, and developing GI strategies for controlling urban pollutants are currently lagging. Furthermore, to our knowledge, no such studies have been done on PCBs, but given the very heterogeneous distribution of PCBs in the landscape (Gilbreath and McKee 2015), these chemicals may be representative of a class of contaminants that differ greatly to suspended sediments and nutrients that tend to be more ubiquitous in the environment and better studied.

To fill in these gaps, the objectives of this study were to (1) develop and demonstrate a holistic approach that can be used to determine optimal selection and placement of GIs for reducing stormwater pollution in urban watersheds; and (2) provide a useful demonstration of what can be done in other urban watersheds in dealing with PCBs and potentially other sediment-bound pollutants. Specifically, this study used NSGA-II coupled with SWMM to find near-optimal combinations of GIs that maximize PCB load reduction and minimize total relative cost. The outcomes from this analysis can be used as a basis to develop watershed-scale GI master plans to help guide long-term planning and implementation of GIs for nonpoint source pollution control.

Study Area

The Guadalupe River Watershed is located in the Santa Clara Valley basin and drains to Lower South San Francisco Bay (Fig. 1). The watershed is the fourth largest in the Bay Area with approximately 414 km^2 of total drainage area. The Guadalupe Watershed has a mild Mediterranean-type climate generally characterized by moist, cool wet winters and warm dry summers. Rainfall and runoff follows a seasonal pattern with a pronounced wet season that generally begins in October or November and can last to April or May, during which a mean of >93% of the annual rainfall and runoff occurs (McKee et al. 2017). The primary focus of this study is the lower part of the watershed that excludes upstream watersheds and all areas upstream from the reservoirs where gauge data are available to define the boundary conditions of the model domain (Fig. 1).

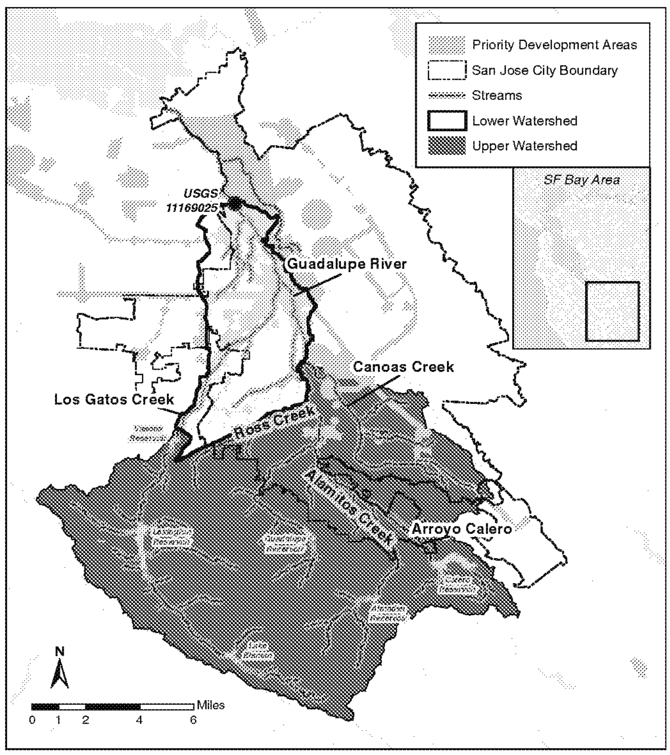

Fig. 1. Guadalupe River Watershed and study area. (Map data from Esri, HERE, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community; City of San Jose; Association of Bay Area Governments; National Elevation Dataset; and National Hydrography Dataset.)

The resulting study area is referred herein as the Lower Guadalupe River watershed and has an area of 7,531 ha.

GreenPlan-IT

GreenPlan-IT, a planning tool that was designed to support the cost-effective selection and placement of GI in urban watersheds, was used for this study. GreenPlan-IT comprises a geographic information system (GIS)–based GI site locator tool, a modeling tool, an optimization tool, and a GI implementation tracking and reporting tool (Wu et al. 2018). For this study, the first three tools were utilized.

The GIS-based site locator tool was used to identify potential GI locations that serve as constraints for the optimization tool. The tool combines the physical properties of different GI types with regional and local GIS data and uses these data, through an identification, ranking, and weighting process, to locate potential GI locations at a watershed scale. The modeling tool, built on the USEPA's SWMM5, was used to establish baseline flow and PCB loads and quantify any reduction made from GI implementation across different areas within the watershed. Within GreenPlan-IT, the modeling tool serves as a subroutine to the optimization tool. During the optimization process, the optimization tool will command the modeling tool to evaluate GI performance and pass that information back. The SWMM was selected because it is a public domain, dynamic rainfall-runoff simulation model suited to simulating runoff quantity and quality from primarily urban areas (Zhang and Guo 2014; Baek et al. 2015; Park et al. 2015). More importantly, SWMM has the capacity to simulate the hydrologic performance of seven green infrastructure types (bioretention cell, rain garden, green roof, infiltration trench, permeable pavement, rain barrel, and vegetative swale), which makes it possible to link GI performance to specific GI designs and locations—a key element in the optimization approach. Since PCB removal by GI is primarily through filtration and retaining and infiltrating water volume, the reduction of PCB load can be estimated as a result of changes in flow, thereby providing water quality performance of GI options. The optimization tool uses NSGA-II (Deb et al. 2002) to evaluate the benefits (runoff and pollutant load reductions) and costs associated with various GI implementation scenarios (type, location, number) and identify the most cost-effective options that satisfy user-defined management goals.

Optimization Algorithm

Belonging to the family of evolutionary optimization techniques, NSGA-II is among the most efficient and widely used multiobjective optimization algorithms capable of producing optimal or near-optimal trade-off solutions among competing objectives (Deb et al. 2002). NSGA-II incorporates a nondominating sorting approach that makes it faster than any other multiobjective algorithm. In NSGA-II, solutions are sorted on the basis of the degree of dominance within the population and a solution that is not dominated by any other solution has the highest ranking. In addition, the algorithm employs a crowded-comparison operator to preserve diversity along the Pareto-optimal front so that the entire Pareto-optimal region is found. Deb et al. (2002) provided a detailed mathematical description of this algorithm.

NSGA-II has gained popularity in recent years and showed superiority over other multiobjective evolutionary algorithms in solving complex environmental optimization problems. A number of studies employed NSGA-II to guide the selection and placement of best management practices to reduce water quality degradation (USEPA 2009; Maringanti et al. 2009, 2011; Rodriguez et al. 2011; Zare et al. 2012; Ahmadi et al. 2013).

Method

The optimization approach required the establishment of a baseline condition for the study area and three components as inputs to the NSGA-II algorithm to evaluate the objective functions of any given GI combination. The three inputs were (1) GI physical attributes; (2) GI costs; and (3) constraints on GI locations. A two-objective (cost and PCB load reduction) optimization problem was then formulated that could be solved through the programmatic implementation of NSGA-II.

Establish Baseline Condition

To ensure the establishment of a representative baseline condition for the study area, the Lower Guadalupe River Watershed was delineated into 151 subwatersheds, and SWMM was calibrated for hydrology for the USGS Gauge Station 11169025 near the mouth of the Guadalupe River (Fig. 1) for 2010–2011. Overall, the hydrologic calibration was deemed good, as measured by mean error for total storm volume of -4% ($<|10\%|$) and Nash-Sutcliffe model efficiency (Nash and Sutcliffe 1970) of 0.97 (>0.7), both statistics well within acceptable criteria.

PCB concentrations were simulated using the water quality module of SWMM, which employs buildup and wash-off functions to estimate pollutants associated with stormwater runoff from each land use. The parameters of pollutant buildup and wash-off functions need to be set through calibration with empirical data. As in most modeling studies of this nature, contaminant data tend to be limited, and only 19 samples were collected for PCB concentrations during winter storms in Water Year 2010 (McKee et al. 2017). Therefore, a weight-of-evidence approach was used to provide a reasonable assurance for the PCB simulation, in which the parameters of pollutant buildup and wash-off functions were fine tuned to reflect the difference in PCB loading from each land-use category described by Mangarella et al. (2010), as well as to ensure the modeled PCB concentrations were within the range of observed data and the modeled load matched the observed load for Water Year 2010.

The calibrated SWMM was used to generate flow and PCB loads under a 2-year, 24-h storm of 4.7 cm to serve as the baseline from which the effectiveness of any GI scenarios were estimated. Although the model was validated for the Lower Guadalupe River Watershed, only a portion of it, downtown San Jose, California, was selected for optimization because this is a primary focus area for redevelopment and therefore where future GI retrofit and implementation are planned to offset any impacts of planned new and redevelopment. The selected area covers 53 of the 151 subwatersheds with a total area of 1,740 ha (Fig. 2).

GI Representation

For the purposes of initial methodology development and refinement, three GI types—bioretention, infiltration trench, and permeable pavement—were selected for inclusion in this study based on stakeholder input, stormwater permit requirements, and an understanding of practices commonly used in the San Francisco Bay Area, but additional GI types have been added in other Bay Area applications. The primary processes for these three GI types are filtration and infiltration, which helps slow stormwater down and reduce runoff volumes, remove pollutants, and support stream baseflow. Key configuration parameters for each GI feature are summarized in Table 1. For this study, in order to simplify the optimization process, each GI type was assigned a typical size and design configuration that remained unchanged during the optimization process. The decision variables were therefore defined as

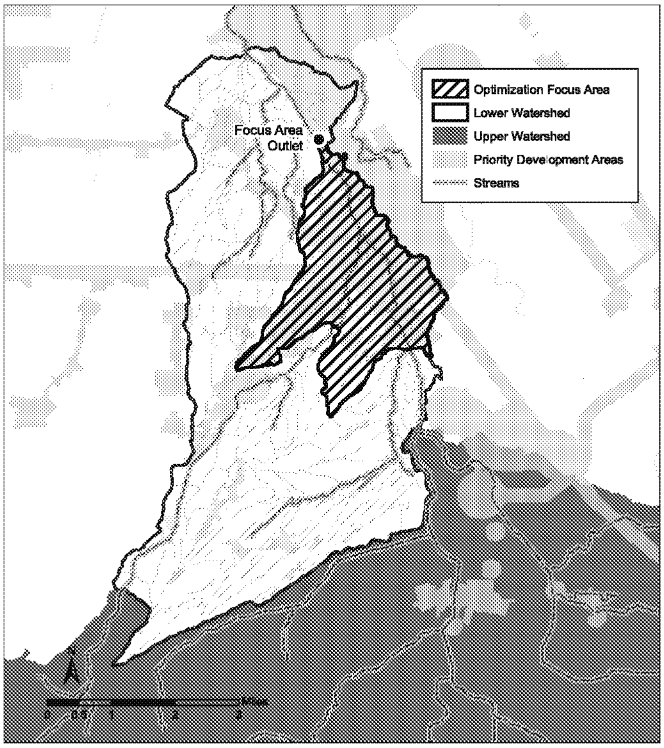

Fig. 2. Optimization focus area. (Map data from Esri, HERE, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community.)

Table 1. GI representation in optimization procedure

Layer	Parameter	Bioretention	Infiltration trench	Permeable pavement
Surface	Area (m^2)	93	46	465
Growing media	Depth (cm)	45.7	N/A	N/A
	Porosity	0.41		
	Conductivity (cm/h)	12.7		
	Suction head (cm)	6.1		
Pavement	Thickness (cm)	N/A	N/A	10.2
	Void ratio			0.18
	Permeability (cm/h)			12.7
Storage	Height (cm)	30.5	91.4	30.5
	Void ratio	0.54	0.54	0.67
	Conductivity (cm/h)	2.5	2.5	2.5
Underdrain	Drain coefficient (cm/h)	1.3	1.3	1.3
	Drain exponent	0.5	0.5	0.5

the number of fixed-size units of each GI type. As such, the configuration of each GI will affect its performance and thus how they are utilized during the optimization process.

GI Costs

Implementing GI at the landscape scale incurs many costs ranging from permitting, traffic control, and construction to maintenance and operation. Considered for this study were costs associated with construction, design and engineering, and maintenance and operation over a 20-year life cycle. In general, the small amount of information that was available indicates a wide variation in costs in relation to site-specific characteristics, design configurations, and other local conditions and constraints, such as socioeconomics. GI cost information was collated from the City of San Jose (Bryan Apple, personal communication, 2014), San Francisco Estuary Partnership (SFEP) (Josh Bradt, personal communication, 2014), and Puget Sound stormwater BMP cost database (Herrera Environmental Consultants 2013b) (Table 2). In the end, the cost data from the City of San Jose were used to reflect local conditions. A unit cost approach was used to calculate the total relative cost associated with each GI scenario. Cost per unit surface area was specified for each GI type based on the total cost and designed surface area of each feature. The total relative cost of any GI scenario was calculated as

Table 2. Unit cost for each GI type

Sources	Construction ($\$/m^2$)	Design (%)	Annual operation and maintenance	Total cost ($\$/m^2$)
		Bioretention		
City of San Jose	—	25	\$7.0	1,120
SFEP	958–3,197	25	\$2.8	1,270–4,682
Washington BMP database	340	67	\$1.3	593
		Infiltration trench		
City of San Jose	—	22	\$9.9/m	970
Washington BMP database	—	—	—	1,033
		Permeable pavement		
City of San Jose	—	22	\$9.9/m	365
Washington BMP database	155	63	—	253

$$\text{Total cost} = \sum(\text{number of each GI type} \times \text{unit cost} \times \text{surface area of each GI type}) \quad (1)$$

Constraints on GI Locations

For each GI type, the number of possible sites was constrained by the maximum number of feasible sites identified on the basis of suitability criteria including physical constraints and watershed characteristics. The suitable sites for placement of GI were identified by the GreenPlan-IT site locator tool. The tool provided the total area of feasible sites for each GI type, and the number of feasible sites was estimated as the area divided by the surface area of each GI.

Depending on the sizing criteria, the total area that can be treated by GI within each subwatershed also imposed implicit constraints on how many GI installations are possible within a subwatershed. After review of the GI design guidance manual (San Mateo Countywide Water Pollution Prevention Program 2009) and through discussion with local stormwater experts, a sizing factor (defined as the ratio between GI surface area and its drainage area) for each GI type was specified: 4% for bioretention and infiltration trench, and 50% for permeable pavement. During the optimization process, the number of GI units were adjusted when their combined treatment areas exceed the available area for treatment within each sub-watershed.

Optimization Problem Formulation

The objectives of the optimization problem were to (1) minimize the total relative cost of GI implementation, and (2) maximize the total PCB load reduction at the outlet of the focus area. The decision variables were defined as the number of fixed-size units of the distributed GI types. For each applicable GI type, the decision variable ranged from zero to a maximum number of potential sites that were identified by the GIS site locator tool. Mathematically, the optimization problem can be expressed as

$$\text{Minimize} \sum_{i=1}^{n} \text{cost}(\text{GI}_i)$$

$$\text{Maximize PCBs load reduction}$$

$$\text{Subject to } n \leq N_{\max}$$

where GI_i = set of GI configuration decision variables associated with location i; and $N_{\max}$ = maximum number of feasible sites.

Total relative cost as calculated from Eq. (1) for each GI combination was used to compare the results. The NSGA-II operational parameters, including population size, number of generations, and crossover and mutation rates, define the search algorithm and have great impact on optimization results. The final decision on the parameters took into account the values used in Deb et al. (2002), as well as the consideration for the optimization problem complexity and model run time. Several combinations of different population size and number of generations were also tested to identify the optimal parameter values. In the end, the key NSGA-II parameters were set with number of generations = 200, population size = 100, crossover probability = 0.9, and mutation probability = 0.1, mostly consistent with the recommendations of Deb et al. (2002).

Sensitivity Analysis

Previous studies (USEPA 2011; Herrera Environmental Consultants 2013a) suggested that the optimization process and resulting solutions are highly sensitive to GI cost and sizing criteria. Just as the optimization results are driven by the specified optimization objective, cost effectiveness is driven by the associated cost assumptions and modeled GI performance. Sensitivity testing of both cost and sizing assumptions were performed to explore the implications of these GI characteristics on optimization results.

GI Cost Sensitivity

A GI scenario with high-end cost estimate based on the regional data was run to test the sensitivity of GI cost and examine the uncertainty in the resulting cost estimate. In this scenario, the cost for bioretention was based on the average of six projects in the San Francisco Bay area, and the costs for infiltration trench and permeable pavement were provided by the City of San Jose for projects with a more complex design. Table 3 lists the unit cost specified for the sensitivity analysis scenario.

Table 3. Unit cost for each GI type for sensitivity analysis scenario

GI feature	Local cost ($/m^2)	High cost ($/m^2)
Bioretention	1,120	1,475
Infiltration trench	970	1,895
Permeable pavement	365	700

GI Sizing Criteria Sensitivity

The amount of watershed area drained to GI installations is another key assumption that influenced the modeled performance of GI practices. For this study, a sizing factor of 4% of drainage area was used for bioretention and infiltration trench, and 50% for permeable pavement. However, the methods allowing for selecting and sizing GI installations to meet permit requirements vary in complexity and can result in a wide variety of designs under site-specific conditions. To test the sensitivity of the GI sizing criteria, the sizing factors for bioretention and infiltration trench were increased to 6% and 8%, respectively, while permeable pavement was kept at 50%.

Results and Discussion

Cost-Effectiveness Curves

The optimization process outputs the optimal solutions along a cost-effectiveness curve. The curve relates PCB removal efficiency to various combinations of GI throughout the watershed and their associated cost. Fig. 3 illustrates the optimal trade-off between implementation cost and PCB load reduction. All individual solutions are plotted together, with the optimum solutions forming the left and uppermost boundaries of the search domain. Each point along the cost-effectiveness curve represents a unique combination of the number of bioretention units, infiltration trenches, and permeable pavement sites across the study area, and can be analyzed in terms of the magnitude of build-out throughout each subwatershed.

Fig. 3 shows a wide spread of GI solutions for PCB load reductions. At the same level of cost, the percentage removal could vary as much as 30%, while for the same level of pollutant reduction the difference in total relative cost could be well over $100 million between an optimal solution and a nonoptimal solution. This highlights the benefit of using an optimization approach to help stormwater managers identify the most cost-effective solution for achieving flow and water quality improvement goals within a limited budget. The slope of the optimal frontier in Fig. 3 represents the marginal value of additional GI installations, and the decreasing slope of the frontier indicates diminishing marginal returns associated with an increasing number of GI installations as reflected in the increasing cost. For example, the curves suggests that a 40% PCB removal can be achieved with about $100 million dollars, but only 20% additional PCB removal can be expected for the next $100-million-dollar investment. This makes sense given the heterogeneous nature of PCB sources and a relatively large variation in PCB loads across this urban landscape (Gilbreath and McKee 2015; McKee et al. 2017). After treating the most polluted areas,

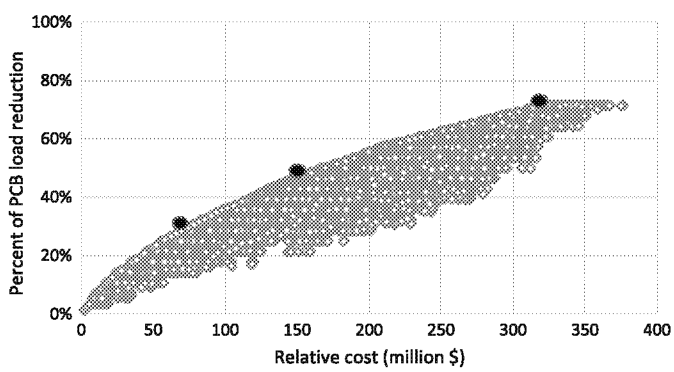

Fig. 3. PCB cost-effectiveness curve.

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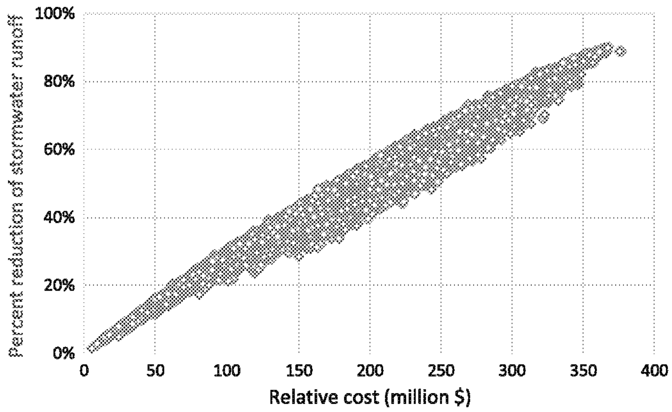

Fig. 4. Runoff cost-effectiveness curve.

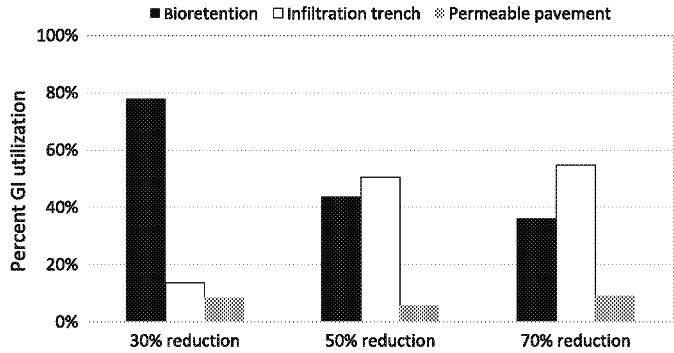

Fig. 5. Percentage of each GI type selected for three optimal PCB load-reduction solutions.

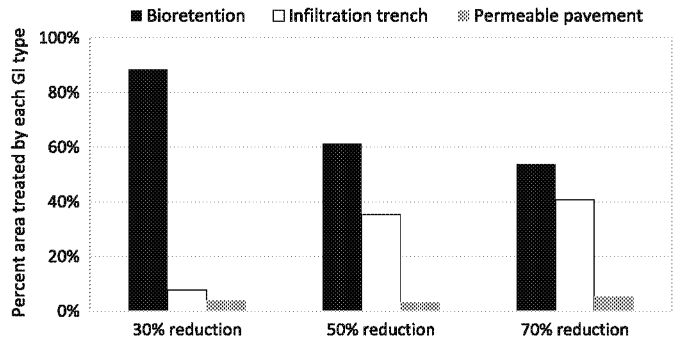

Fig. 6. Percentage of area treated by each GI type for three optimal solutions.

subsequent implementation of treatment measures will need to be placed in less polluted areas, and therefore the load available to treat will be less, resulting in a gradual but decreasing efficiency over time and an increasing cost per unit mass treated. The maximum reduction achievable appears to be around 70%, after which the curve starts to level off and little reduction can be achieved with additional investment. With the help of this information, decision makers can set realistic goals on how much PCB reduction can be achieved and the level of investment required, as well as determine at what point further investment on GI will become less desirable as the marginal benefit decreases.

Since PCB loads are primarily reduced through settling and filtration stormwater runoff, it is also of interest to examine the trade-off curve between implementation cost and runoff volume reduction as ancillary results of the optimization (Fig. 4). The trade-off curve for runoff exhibits a relatively tight range of solutions due to the comparatively homogeneous nature of runoff production compared with PCB load in the study area. The model calibration shows that spatial variability in runoff production is about threefold in this highly urbanized watershed where subwatersheds have a similar level of imperviousness. The maximum achievable runoff volume reductions at the outlet of the study area, given the objectives and constraints associated with the study, was estimated to be about 90% (Fig. 4). These solutions are optimized for PCB reduction and therefore not necessarily optimal for runoff reduction. If runoff reduction were used as the optimization objective, the resulting cost-effectiveness curve for runoff would be different and less optimal for PCB reduction.

GI Utilization and Spatial Distribution

The types of practices associated with each point along the cost-effectiveness curve provides insight into the reasoning and order of selecting individual practices. Three solutions, with 30%, 50%, and 70% of PCB reduction (Fig. 3, three enlarged dots), were selected from the PCB cost-effectiveness curve for further detailed evaluation. Each point along the cost-effectiveness curve corresponds to a unique GI combination. For a given solution, the selection of GI can be (1) evaluated in terms of the magnitude of build-out and percent utilization; and (2) analyzed spatially in terms of GI selections throughout each subwatershed.

The percent utilization of each GI type among the three types is quantified for each selected solution (Fig. 5). At 30% load reduction, bioretention is the most effective GI and accounts for 78% of total GI selected, while infiltration trench accounts for 14% and permeable pavement 8%. As the level of reduction increases, infiltration trench becomes more cost effective and its utilization is increased from 14% at the 30% reduction scenario to 55% at the 70% reduction scenario. For all three reduction scenarios, permeable pavement appears to be the least cost effective and the amount of utilization stays less than 10% due to its low treatment ratio and small number of feasible sites associated with its large surface area. Within the optimization process, the selection of each GI type is largely driven by its respective representation (Table 1) and unit cost. Changing any of these will change how each GI type will be utilized for any given solutions.

The percent utilization of each GI type can also be viewed in terms of area treated (Fig. 6). At 30% load reduction, nearly 90% of areas are proposed to be treated by bioretention, 8% by infiltration trench, 4% by permeable pavement. As the level of load reduction increases, the percent of area treated by infiltration trench increases and bioretention decreases, and by the time load reduction reaches 70%, infiltration trench is selected to treat 40% of available areas. For all three scenarios, bioretention is selected to treat more than 50% of the available areas, making it the most cost-effective GI among the three types. In contrast, permeable pavement only treats 5% of areas, and therefore appears to be the least cost-effective GI.

While these results seem logical and provide excellent guidance, it is important to emphasize here that this observation should be interpreted within the context of specific configurations for each GI type as defined in this study. If any of these design criteria were to change, a different set of guidance would emerge. Therefore, it is important to work with managers and local stakeholders to work through the ramifications of these decisions as part of the planning process and try to match the model physics reasonably well with

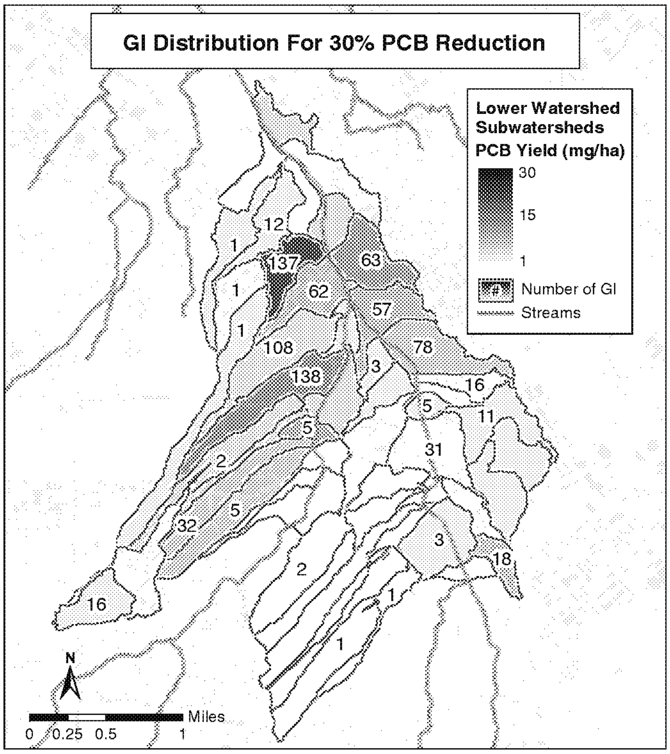

Fig. 7. Number of GIs identified for each subwatershed. (Map data from Esri, HERE, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community; National Elevation Dataset; and San Francisco Estuary Institute.)

the physics of the GI types that will eventually be retrofitted into the urban landscape after the planning process is complete.

GI utilization results can be mapped by subwatershed to gain insight into the optimal spatial placement of these practices derived under the defined objective and constraints. Fig. 7 shows the number of GIs identified at each subwatershed for the 30% load-reduction scenario. In general, the optimization process identified more GI needed at the areas with high PCB yield and runoff (darker area), where GI could be most efficient. The total number of GI locations identified are dependent on the unit size used for each GI type, and the optimal solutions will be different in GI numbers and compositions if a different design for any GI is used.

The optimization results must be interpreted in the context of specific problem formulation, assumptions, constraints, and optimization goals unique to this case study. If one or more assumptions are changed, for example, the optimization target was designed as reducing total runoff volume instead of PCB loads, the optimization might have resulted in a completely different set of solutions in terms of GI selection, distribution, and cost. Also, because of the large variation and uncertainty associated with unit GI cost information, the total relative cost associated with various reduction goals calculated from the unit cost do not necessarily represent the true cost of an optimum solution for the basin evaluated and are not transferable to other basins. Rather, these costs should be interpreted as a common basis to evaluate and compare the relative performance of different GI scenarios. Implementation costs will likely be much lower than the modeling would predict because GI can be implemented as part of existing or enhanced capital improvement plans and transportation projects, through batch design and construction where large areas of the urban landscape are retrofitted at once, as a component of new development, and perhaps through public–private partnerships.

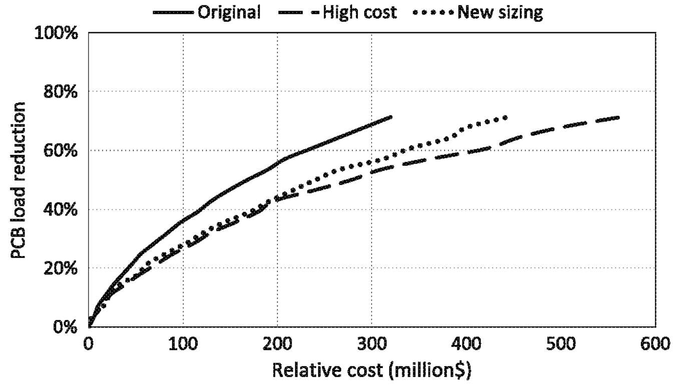

Fig. 8. Comparison of cost-effectiveness curves of sensitivity analysis.

Sensitivity Analysis Results

As expected, the sensitivity results suggest that assumptions made with GI cost were highly influential on the optimization results. Fig. 8 shows three versions of cost-effectiveness curve: the original scenario, high-cost scenario, and new sizing scenario. Varying the unit cost at the same level of reduction results in different relative costs and GI combinations and vice versa. For instance, at the 30% PCB reduction level, the total relative cost was estimated to be around \$80 million with the original unit cost, and increase to \$130 million with high cost. And the optimal combinations of GI types and numbers are also different. The difference in total implementation cost demonstrates the sensitivity of GI cost and suggests that the range of probable assumptions could significantly increase the calculated implementation cost in the study area. As such, reliable and accurate local cost information should be used to drive the optimization process wherever possible. However, despite this illustration and the importance of working with managers and stakeholders closely as the modeling assumptions are developed, given the planning nature of the tools presented here, it is important to communicate that it is not the total estimated cost that is important but rather identifying the most cost-effective GI combinations that minimize relative cost for maximum benefits.

Similarly, with new sizing criteria, the cost is evidently higher at all levels of PCB load reduction (Fig. 8, dashed line). Since two GI types are now designed to treat a smaller amount of impervious area, the number of GI installations required to reduce the same amount of PCB loads will increase, which translates to higher cost. And the cost difference between two scenarios generally grows wider as the level of load reduction increases, suggesting the higher the load reduction, the more GI will be required under new sizing criteria.

Conclusions

An optimization framework that couples an optimization approach (NSGA-II) with a watershed model (SWMM5) was developed to identify optimal GI solutions for reducing PCB loads at the watershed level. Three GI types with specific designs and unit costs were used to simulate potential PCB load reductions associated with various combinations of GI implementation. The result of the optimization procedures described was a cost-effectiveness curve of optimal management cost for various levels of PCB reductions. A wide spread between the optimal frontier and intermediate solutions generated during the optimization process as well as diminishing marginal returns associated with an increasing number of GI installations highlight the benefit of using an optimization approach to help to identify the most cost-effective solution for achieving a certain reduction goal or within a limited budget. Such an analysis provides stormwater managers with a wide range of near-optimal retrofit and buildout scenarios that take into consideration environmental benefits and economic costs of various GI alternatives and could be used to inform policy decisions regarding future stormwater management investments.

Sensitivity analysis of both GI costs and sizing criteria suggest that assumptions made regarding those parameters were influential on the optimization results. Therefore, wherever the approach is applied, reliable local cost information and site-specific design should be used to ensure a successful and meaningful application, and sensitivity analysis and evaluation of cost control measures or economies of scale are recommended.

The developed integrative methodology provides the decision makers with important information regarding trade-offs among competing objectives. The watershed approach is particularly advantageous in that it helps develop more comprehensive GI implementation plans that take into account the physical interaction and dynamic processes occurring within a watershed. The methodology can be used to comply with National Pollutant Discharge Elimination System (NPDES) stormwater permit requirements as well as address load reduction needs identified in TMDLs.

Finally, it is crucial to interpret the optimization results within the context of each specific application, including problem formulation, model assumptions, and sensitivity of GI parameters. Furthermore, since the model baseline is the foundation for comparative assessment of various GI scenarios, establishing a representative baseline condition with a high level of confidence is critical to ensure the optimization results are meaningful and becomes especially important when cost-benefit optimization of future management objectives is a primary focus of the modeling effort.

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